

Application of artificial neural networks in global climate change and ecological research: An overview

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Fields that employ artificial neural networks (ANNs) have developed and expanded continuously in recent years with the ongoing development of computer technology and artificial intelligence. ANN has been adopted widely and put into practice by researchers in light of increasing concerns over ecological issues such as global warming, frequent El Niño-Southern Oscillation (ENSO) events, and atmospheric circulation anomalies. Limitations exist and there is a potential risk for misuse in that ANN model parameters require typically higher overall sensitivity, and the chosen network structure is generally more dependent upon individual experience. ANNs, however, are relatively accurate when used for short-term predictions; despite global climate change research favoring the effects of interactions as the basis of study and the preference for long-term experimental research. ANNs remain a better choice than many traditional methods when dealing with nonlinear problems, and possesses great potential for the study of global climate change and ecological issues. ANNs can resolve problems that other methods cannot. This is especially true for situations in which measurements are difficult to conduct or when only incomplete data are available. It is anticipated that ANNs will be widely adopted and then further developed for global climate change and ecological research.

global change, ecology, artificial neural network, nonlinear problem

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In recent years, global climate change has become a focus of attention for governments, scientists, and the public at large. Related research in numerous domains has been conducted and remarkable progress made in recent years. Global climate change is primarily a result of global warming, frequent El Niño and La Niña events, and atmospheric circulation anomalies. The global average temperature has increased by approximately 0.6°C over the past 100 years and is projected to continue to rise at a rapid rate. In addition, global atmospheric CO₂ concentrations have risen by nearly 38% since the pre-industrial period and are projected to surpass 700 μmol mol⁻¹ by the end of this century [1].

Taking “global warming” as a prominent indicator, climate change may effectively alter ecosystem structure and function. Over the years researchers throughout the world have undertaken numerous observations and experiments, and have accumulated and analyzed much data on climate change. It is necessary to make full use of this data to provide reasonable modeling predictions in relation to the effects of climate change for scientific usage and government policymaking initiatives. Artificial neural networks (ANNs) are a unique tool for the special training of data, model calibration, simulation, and prediction. It has developed into an effective method of study. The neural network possesses a strong capacity to learn and is a convenient tool that can handle complex nonlinear systems and nonlinear relation-

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ships that are difficult to describe using mathematical analytical expressions. In theory, a three-layer neural network model can provide any nonlinear mapping. Because an ecosystem is a complex nonlinear system, an ANN is an effective method to describe an ecosystem and its various characteristics.

ANNs have developed rapidly in their applications to global climate change and ecology. This approach has increasingly been applied to hydrology, forest ecology, and changes in urban air quality. This paper introduces ANN methods and reviews the application of ANNs to global climate change and ecology in recent years (primarily post 2000). The paper also proposes prospects for future applications and directions for future developments.

1 Artificial Neural Network

1.1 Introduction

ANNs are mathematical algorithmic models that imitate the neural network behavior characteristics of animals, and carry out parallel distributed information processing. These networks rely on the complexity of a system by adjusting large numbers of interconnected relationships between nodes for the purpose of processing information.

McCulloch and Pitts established a neural network model in 1943 that they designated the McCulloch-Pitts (MP) model. They expropriated the formal neuron network structure and described it mathematically within the context of the MP model, showing that a neuron can execute logical functions, and initiating the era of artificial neural network research. With advances in computer technology, John Hopfield, a faculty member of the California Institute of Technology in the early 1980s, established the famous Hopfield neural network model [2]. Because this neural network model incorporated the Liapunov function (energy function) to ascertain proof, it possesses an associative memory ability and can undertake problem solving optimization. This model also solved the travelling salesman problem (TSP) and provided a new method for solving optimization problems, as well as offering an important basis for neural computer research and development [3]. During the period from 1986 to 1988 psychologists McClelland and Rumelhart proposed the famous multi-network backpropagation (BP) algorithm. This algorithm remains one of the most widely-used neural network learning algorithms today. Remote sensing image analysis and classification have been using traditional statistical methods such as minimum distance and the maximum likelihood classifier [4]. These methods have their own limitations, particularly regarding the integration of different data types and the pixel distribution hypothesis of samples. Using ANNs can overcome the shortcomings of statistical classification and improve classification performance. In the past decade, ANNs have been the most popular classification tool for non-parametric land

classification by satellite imagery [5–8]. Network algorithms are more abundant today and are found in the back-propagation algorithm, the simulated annealing algorithm, the genetic algorithm, competitive learning, inter alia. Together, they all contribute to the network algorithm system in use today. The application of neural network models can determine function approximation, forecasting, data clustering, pattern recognition, and optimization calculation. Except for the improvement of the algorithm itself, the development of ANNs can also be combined with various other methods such as a neural network-decision tree combination used for forecasting and analysis, and an ANN combined with the System Dynamics (SD) and Cellular Automata (CA) models. Moreover, it can be applied to different subjects and disciplines, such as information ecology. The application of neural network is in great demand.

Artificial neural networks include three basic processing elements: unit, network topology, and training rules [3].

The ANN processing unit is the basic unit of operation. It simulates the functions of neurons. A processing unit possesses multiple input and output paths. The role of information transfer is to enter ports while outputs carry the information from one processing unit to the next. As shown in Figure 1, x is the neuron input, w is the adjustable input weight, and θ is offset signal used for modeling the neurons excitation threshold. $u(\cdot)$ and $f(\cdot)$ are the basic function and activation function, respectively.

Network topology determines the route and approach of information transfer between each processing unit and layer. At present, dozens of neural network topologies are available for application. Because a three layer backpropagation neural network model (Figure 2) can simulate any continuous function [9], most related studies apply it. Moreover, simple neural networks are explained easily, training speeds are standardized, and rarely is anastomosis a factor [10].

Training is an essential feature of a neural network. Required accuracy is achieved using repeated training and adjustment. Weights and sums of data typically use the transfer function $f(x)$, as does training of a network system for pattern recognition to manage the weighted value. The output value is then obtained using the conversion function. Finally, the classification result assigns the maximum weight category for the input data ownership category [11].

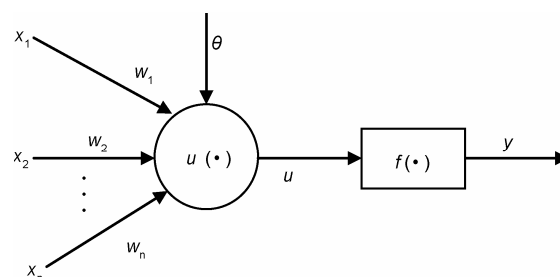


Figure 1 General neuron model.

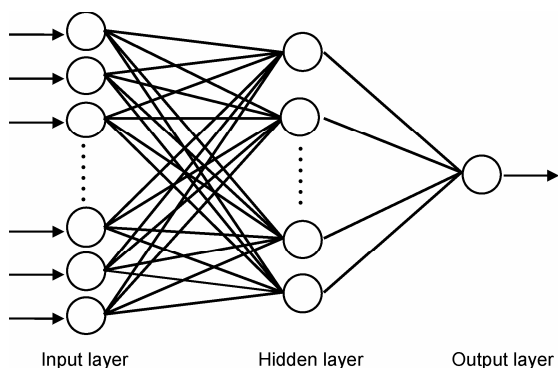


Figure 2 Neural network topology.

Similar to the mechanisms of the brain, a neural network process can be divided into two primary phases to accomplish the task at hand [3,11]: the first stage is the study period or the stage in which self-improvement occurs. During this stage, a network modifies synaptic weights under certain learning rules and works to make the measure function reach a minimum. Moreover, the state of the calculating unit remains unchanged, and all the weights can be modified by training. The second stage is the implementation period where a neural network processes input data and generates corresponding output data. At this point the connection weights are fixed and the calculation unit has reached a steady state condition.

1.2 Application software

A large number of neural network-specific or generic software has been introduced, providing useful tools for the application of neural networks. Among these, NeuralWare Inc.(www.neuralware.com) developed NeuralWorks Predict and NeuralSight. They are advanced neural network model development packages, and are the most sophisticated commercial neural network products available. They can be applied to the training, testing, and application of neural network models developed for forecasting, classification, and aggregation. Neural networks and genetic algorithms, and fuzzy logic and statistical software, were combined within the software, providing a stable solution for more extensive application.

The Neural Network Toolbox for use with MATLAB and Neuralworks Professional II/Plus platform (version 5.20), developed by NeuralWare and NeurSolution (version 3.0) from NeuroDimension Inc. [12] are the most widely-used neural network applications.

2 Application of artificial neural networks to global climate change and ecology

2.1 Effect of climate change on hydrological-ecological environments

Clair and Ehrman applied an ANN model to evaluate for the

first time the influence of climate change on riverine ecosystems and flow, and the application of ANNs to climate change and hydrological ecosystems has been advancing in recent years [13]. To analyze climatic factors that influence runoff, Chen et al. [13] used an ANN model to build up the effectual relationship between monthly precipitation, temperature, and runoff from data acquired from a station situated on Bayinbuluke. Based on regional climate models, they applied potential climate change scenarios under conditions of increasing CO₂ by a magnitude of two in northwestern China, and estimated the effect of climate change on surface runoff. Results show that annual runoff increased from approximately 6.7% to 25% when temperature increased by approximately 1 to 3°C, and that annual runoff increased from approximately 1.4% to 11% when precipitation increased from approximately 5% to 25%. Therefore temperature has a greater influence on local runoff than rainfall. Although rising temperatures and increasing rainfall help ease the current state of drought in northwestern China, the increase in runoff concentrated within a 7- and 8-month period increases the risk of flooding during the summer months, to the extent that it will change the mode of development and project planning in relation to the use of water resources. Furthermore, Zou and Wang [14] have verified the validity of applying a BP neural network model to predict the effectiveness of river water quality. Their results show that considerable errors in long-term predictability of river systems exist during the continuous forecasting of water quality, while short-term predictability generates fewer errors. Short-term predictability, however, requires an increase in data acquisition and takes more time to calculate.

Seasonal temperature and precipitation changes have an important effect on the research of carbon, phosphorus, and nitrogen in watershed systems. Holmberg et al. [15] generated daily temperature and precipitation values between the years 2040 and 2069 using CLIGEN and modeled daily total organic carbon (TOC), total nitrogen (N_{tot}), and total phosphorus (P_{tot}) in a river system using an ANN. They were able to simulate the flux under future climate change scenarios, and found that TOC, N_{tot}, and P_{tot} flux increased in stream water and that this condition was dependent primarily upon changes in the amount of runoff rather than concentrations. Although the ANN model did not obtain all extreme values in relation to TOC, N_{tot}, and P_{tot} flux in stream water, its output was consistent with observations for most of the dynamic values. A clearer division between the effects of temperature and runoff should be identified when selecting network parameters. Particularly in relation to dry conditions, the annual output value is more important than the concentration of extreme values acquired using observation and through simulation experiments. Moreover, Nour et al. [16] designed an ANN model that can predict non-standard river flow (where the daily flow has not been monitored fully) and P_{tot} concentration.

The influence of climate change must also be considered

in karst regions. Karst aquifers, however, are highly heterogeneous and there is little monitoring data from these regions. For the sustainable utilization and conservation of karst groundwater, it is therefore necessary to simulate spring flows to acquire a better overall understanding of karst hydrology. Hu et al. [17] developed a parsimonious model that simulates accurately spring discharge using an ANN model, and they applied this model to the Niangziguan Springs. Although research has shown that the short-term application of ANNs is more unstable than long-term applications, the ANN model performed better compared with a earlier time lag linear model.

Taking the entire route choice into account, total runoff does not imply all runoff generated from individual subcatchments that choose the path of linear superposition. ANNs are an effective and appropriate nonlinear mapping tool used to research nonlinear transformation. Chen and Adams [18] applied the integration of an ANN combined with conceptual models for rainfall-runoff modeling. Runoff generated from individual subcatchments can be transformed by an ANN to generate runoff at the watershed outlet point. This new method performs better than previous models such as Xinanjiang, SMAR, and Tank, and this research direction has considerable potential. For example, it can be applied to various terrains under various environmental conditions, and continue to build on existing research.

Elshorbagy and Parasuraman [19] used traditional and higher-order ANN to model complex soil moisture dynamics. Simulations demonstrated that ground temperature is the most influential variable for characterizing soil moisture, underlining the strong link that exists between soil thermal properties and the corresponding moisture status. Higher-order neural networks yielded relatively higher correlation coefficients than traditional ANN models in certain soil moisture simulations. Time lag inputs were used to improve model performance and obtain optimum operation capacity. Friedrich Recknagel [20] believes that ANN models can attain a high generalization degree as well as forecasting accuracy after training using time lag time series data. His research has shown that input sensitivity curves using a supervised feedback ANN, combined with component planes using a non-supervised ANN, is an effective approach. We are in agreement with Friedrich Recknagel and feel optimistic regarding neural network usage in the application of ecological informatics through, for example, implementing generic categorical ecosystem hybrid model libraries on a global scale using object-oriented programming and interactive internet access. This direction is highly encouraged.

Chen and Chang [21] have developed a new hybrid ANN model using both the genetic algorithm and the scaled conjugate gradient algorithm in which the feed-forward ANN architecture and its connection weights of neurons are simultaneously identified and optimized. They also verified

the adaptability and reliability of the model within a real-hydrological-time series, and found that its accuracy is superior to that of both the AR and ARMAX models. Lischeid [22] used an ANN to investigate the short-term dynamics and long-term trends of SO_4 within runoff from a forest catchment. This shows that the potential of ANNs is superior to chemical time series analysis. The ANN model can also serve as a tool to calculate water quality parameters. Singh et al. [23] computed that the values of dissolved oxygen (DO) and the biochemical oxygen demand (BOD) using ANN models were in good agreement with their respective measurement values obtained in river water. Moreover, Park et al. [24] reported the application of ANNs for patterning and predicting aquatic insect species richness in running water. With regards to domestic research, Song and Cai [25] developed a comprehensive quantitative assessment model for use in basin water-soil environmental quality valuation in arid areas applying a BP neural network, and a case study of the Shi Yang River located within a basin measuring the highest levels of water resource utilization. The ANN values and actual values were consistent. The study carried out by Song and Cai showed that the model was practical and convenient to use, and could be applied to basin water-soil quality assessment.

ANNs have been used widely in the study of hydrological environments with regards to hydrological forecasting and measurement, the prediction of water quality and other hydrological environmental system components. Present developments are moving in a direction that is compatible with different environments, synchronization, and greater environmental data processing capacity. Song and Cai [25] have attempted to find a common evaluation model that can manage different parts of a comprehensive evaluation of soil and water environments, and Zou and Wang [14] developed a single-river prediction for the continuous prediction of multi-rivers. Research undertaken by Noura et al. [16] allows easy access for all inputs such as the Environment Canada weather database and other such public databases without having to install each individual simulated river flow meter, and their ANN model is an outstanding example of ecosystem complexity and highly-correlated variable modeling.

2.2 Air quality and greenhouse gas emissions

Viotti and Liuti [26] used the BP algorithm and approximately 24 to 48 h of meteorological data and the intensity of automobile traffic to predict concentrations of pollutants in the city of Perugia. Variables monitored were sulfur dioxide, nitrogen oxides (NO , NO_2 , and NO_x), total suspended particulate matter including PM_{10} , carbon monoxide, benzene, ozone, horizontal wind speed, air pressure, moisture, temperature, total sun radiation, automobile traffic, and precipitation. This method works well for predictions within one hour. Prediction capacity decreases for middle range

(24 h) and long-term forecasts, but ANNs still work better than the typical deterministic models now in use. Nagendra and Khare [27] applied an ANN to model the dispersion of NO₂ for automobile exhaust forecasting in the city of Delhi, India. Model inputs consisted of 10 meteorological and six typical traffic variables and data from two air quality control regions (AQCR; AQCR1 and AQCR2). The maximum likelihood of the fitting coefficient of the predicted and observed values of the model was 0.76. Chen and Ma [28] applied wavelet decomposition and reconstruction to determine the annual trend in change of air pollutant concentrations, and established a neural network model to ascertain subatmospheric concentrations of pollutants before predicting atmospheric SO₂ concentrations. To improve upon network generalization they coupled the “stop ahead” and “neural network ensemble” within the programs [29] to optimize the learning process. Ryan et al. [30] applied ANNs to simulate N₂O emissions from a temperate grassland ecosystem.

Barcenas et al. [31] applied neural networks to surface ozone modeling, and simplified models using unbiased sensitivity and pruning techniques. The data used in their study was obtained from the small town of Carcaixent, 40 km south of the city of Valencia, Spain. Network input variables were levels of NO and NO₂ and meteorological parameters such as wind speed, temperature, atmospheric pressure, solar irradiance, and relative humidity. The data were acquired during a consecutive 20-d period from April 1 to April 20, 2002. The output variable was the level of O₃. Sensitivity analysis has shown that the most relevant factors in O₃ concentrations are temperature and solar irradiation while the least important variables are the O₃ precursors (NO and NO₂). It is likely that O₃ may not have been generated within the monitoring area itself but transported by wind from other areas.

The amount of carbon exchange that occurs between vegetation and the atmosphere, the net ecosystem exchange of CO₂ (NEE), is an important factor in relation to carbon sinks and carbon sources that have a considerable effect on terrestrial ecosystems. Accurate NEE estimations and long-term observations in various ecosystems and continued research on NEE spatial distribution and NEE simulation dynamics are critical to understand climate change. He et al. [32] used the close relationship that exists between energy flux and CO₂ flux to simulate the feasibility of CO₂ flux using the ANN method. The study found that CO₂ flux, energy flux, and temperature are all closely correlated, and the accuracy of the simulation was not improved by adding soil moisture as an input variable. This research demonstrates that the application of ANN models can effectively simulate CO₂ flux and can also answer certain questions regarding mechanisms. The integrated approach between the observations of vorticity and remote sensing technology and the energy flux data obtained at regional scales has provided an effective technical approach in terms of the simulation and

analysis of the regional scale spatial patterns of CO₂ flux. Melesse and Hanley [33] applied a multilayer perceptron ANN technique incorporating an error BP algorithm to a CO₂ flux simulation study of three different ecosystems (forest, grassland, and wheat). Temperature (soil and air) and energy flux (latent heat, net radiation, sensible heat, and soil heat flux) were used to train the ANN model and predict the total CO₂ flux. Results show that ANNs can predict successfully observed values where R^2 values are between 0.75 and 0.94. Predictions from forests and wheat fields show greater promise compared with the grassland sites. The significance of this technology is that it estimates either regional or global CO₂ flux from point measurements while incorporating the spatiotemporal budget of CO₂ flux. Papale and Valentini [34] studied eddy fluxes using an ANN to investigate carbon exchange within European forest systems. This study not only performed interpolation using single flux data sites but also used NDVI data to simulate spatial (1 km×1 km) and temporal (weekly) estimates of carbon flux within European forest systems at a continental scale.

2.3 Modeling forest ecosystems, vegetation, and soil change projections

ANN has recently become a popular tool in forest modeling, because it eliminates many difficulties in handling forest data such as nonlinear and non-normal relationships. Forest biomass estimation is an important component in global change research. Wang and Guan [35] attempted to apply the BP and RBF neural networks to estimate forest biomass based upon remote sensing. Results showed that the relative error of both ANN estimation types is less than 15.18% when estimating separate plots, while the maximum relative error of the RBF model does not exceed 10.12%, and the average relative error is only 4.76%. The RBF model, therefore, performs better than the BP model in terms of stability and speed of identification accuracy.

For forest ecosystems, the nitrogen status can be represented by the net nitrification potential (NNP) of forest soils. Ito et al. [36] predicted soil NNP using an ANN model. This ANN model uses ridge-stabilized Gauss-Newton to manage existing data, i.e. to prevent excessive weights caused by overlearning. This particular ANN-based model applied only two soil data properties (the C:N ratio and the maximum water holding capacity) to provide the best NNP prediction. This greatly enhances the simplicity of the practical value of the model for managing forest systems.

Ostendorf et al. [37] used an ANN to study the effects of climate change on tropical rainforest vegetation patterns to understand how vegetation alters within a given climate change scenario. Results demonstrate that small- and medium-sized rain forest vegetation would decrease while medium-sized open forests and woodlands would increase. Predictions for mesophyll vine forests and wet sclerophyll vegetation, however, differ strongly between the different models.

High-resolution soil maps are generally only available for small areas because obtaining these maps using field surveys is time-consuming and expensive. Zhao et al. [38] have recently developed an ANN model to predict soil texture (sand, clay, and silt content) based upon soil attributes obtained from existing coarse-resolution soil maps combined with hydrographic parameters derived from a digital elevation model (DEM). The calibrated ANN model can be used to produce high-resolution soil maps in areas possessing similar conditions without additional field surveys. Root mean square errors between model predictions and field measurements were 4.0 for clay content and 6.6 for sand content. The relative overall accuracy (within $\pm 5\%$ of the field measurements taken) was 88% for clay content and 81% for sand content. Kavdir [39] categorized sunflower, weed, and soil content using an ANN. Moreover, Liu et al. [40] used a BP neural network model to improve the capacity for hyperspectral reflectance to detect changes in roadside tree leaf chlorophyll content.

To facilitate the wide variety of forest land management approaches it is often necessary to draw broad-scale maps of forest attributes. Moisen and Frescino [41] compared five modeling techniques to determine the most suited tool for map tasks given multiple objectives and logistical constraints. The five types of modeling techniques were linear models, generalized additive models, classification and regression trees, multivariate adaptive regression splines, and ANNs. Results show that all techniques proved effective within an automated environment. When their potential mapping capacity was explored using simulations and the advantages of multivariate adaptive regression splines and ANNs over the other three methods in their predictive ability was evident. All five methods demonstrate only minor differences in real data runs.

Hu et al. [42] used an ANN for a near-natural forest system, using as training samples the natural distribution of vegetation types in a typical watershed perimeter. They applied a BP neural network method to identify allocation models for the protection of forest vegetation within a typical watershed. The primary contribution of this model was that it provided an effective method to optimize vegetation types for the protection of forest systems. As an example of the protection of watershed forest vegetation types in terms of area after optimization was carried out, coniferous forests accounted for 4.45 km², broad-leaved forests for 23.56 km², mixed forests for 63.84 km², and shrubbery for 27.57 km². Among them, coniferous forest experienced the largest reduction (73.29%) and broad-leaved forest experienced the largest increase (38.92%). The overall benefits of the protection of forest systems within watersheds have increased. Ooba et al. [43] combined a genetic neural network and an ANN to estimate missing carbon flux data within a dataset by gap-filling on-site measurements. Luo et al. [44] used an ANN to classify a natural forest protection plan, using five planning factors (tree species diversity, rarity, disturbance

degree, channel system protection, and classification management) as inputs to the BP neural network model they developed. All natural forest data collected from the Moershan National Forest Park were used for BP model training and testing. Scrinzi et al. [45] report that they have updated overall forest distribution data for managed alpine stands based upon short-term and long-term findings from neural network models.

Land use and land cover changes are one of the most common factors affecting landscape and ecosystem structures and thus functional and dynamic change. Zhang et al. [46] applied ANN and DEM data to detect vegetation change. Results showed that the application of a modified confusion matrix to assess the detection accuracy of vegetation change is reliable, and combines effectively various NDVI methods and the visual interpretation of data for ground samples. ANNs can improve prediction accuracy using principal component analysis to reduce 14 bands into eight principal components, and DEM and the slope of two additional "bands".

Many ANN and remote sensing technology applications are available. Jensen et al. [47] used both statistical and ANN approaches to model coniferous forest age based upon remote sensing data. Liu et al. [48] used remote sensing imagery and geographic information systems (GISs) combined with ANNs to estimate forest stock volume. Wang and Xing [49] applied a BP neural network to establish a remote sensing-based forest biomass nonlinear model system for the natural forested area of Wangqing, Jilin Province. Zheng et al. [50] combined GISs with ANNs to develop a regional ecotourism suitability assessment model. This particular model possesses a reference value for domestic ecotourism operation and its related evaluation. Yu et al. [51] applied an ANN model to simulate the spatial change of soil organic carbon. To test the accuracy of the ANN model, they compared the correlation between observations of soil organic carbon content and the change value to the ANN model. *R* values were greater than 0.7 compared with approximate *R* values from 0.50 to 0.61 generated by the vast majority of statistical methods.

The abovementioned ANN models have made some breakthroughs in relation to modeling forest ecosystems and vegetation and in relation to changes in soil prediction. The guiding principle of the "black box" issue of the ANN model was highly accurately described by Wang and Guan [35]. When network training is complete, it will be applied to biomass estimates of large areas. The method by Zhao et al. [38] showed that as long as the ANN model in question is trained properly it can be applied to the region in which the model was calibrated or regions that possess similar input parameters. It greatly improved the efficiency of high-resolution soil maps and enlarged the areas under investigation. Yu et al. [51] found that the ANN model approach is a reliable one with which to predict spatial distribution of soil organic carbon. Moreover, the research of

Luo et al. [44] has shown that the neural network approach used in the planning of natural forest protection is feasible. Compared with Campbell et al. [52], McClelland et al. [53], Hepner et al. [54], and Downey et al. [55] in which the application of ANN technology and LTM (Landsat Thematic Mapper) data is solely used for land classification [56], Pijanowski et al. [57], Zhang [58], and Bai et al. [59] used an ANN combined with a GIS to establish land transformation models and apply them in the study of forest change. This improved greatly the use of ANN models for a broad range of applications.

2.4 Other artificial neural network applications in ecology

Photosynthetically active radiation (PAR) is the energy source employed by plant life and the formation of organic synthesis and production. PAR research can guide environmental initiatives and improve crop population structure; however, it is not often measured and must therefore be estimated. Lopez et al. [60] developed a novel approach based upon a simple multilayered feed-forward perceptron approach that has been used to analyze nonlinear relationships between PAR and different meteorological and radiometric variables, to determine their relative relevance. Results indicate that the ANN model, which used global irradiance and solar zenith angle or combined illumination time and the solar zenith angle as input parameters, has yielded the most favorable estimation. Other input parameters such as diffuse scattering radiation intensity, an explicit index, or Perez parameters cannot be used to estimate more accurate hourly PAR, and meteorological parameters such as temperature, relative humidity, and precipitation estimation have almost no effect on PAR. Model performance has been tested and compared with existing empirical complex models. There are important improvements, primarily in the measurement of radiation that is not available or cannot be calculated accurately. The ANN model, therefore, remains a good way in which to calculate hourly PAR.

The quantitative assessment of ecosystem vulnerability and stability is a complex task. Climate change uncertainty, nonlinear relationships between climatic factors and structure, and ecosystem function are the primary challenges in studying the issue. Li et al. [61] applied an ANN model to evaluate the vulnerability of ecosystem response to climate change. Results showed that vulnerability and surface dryness had the highest correlation coefficient (0.985) followed by the annual growth of dominant species (correlation coefficient of 0.979). The correlation coefficients were 0.629 for NPP and the soil carbon density, and 0.577 for the vulnerability index ($P < 0.05$). This preliminary study showed that the application of ANNs to assess ecological systems is feasible and effective. It has advantages of setting the right objectives without applying a unified dimensional model, but selected indicators will face difficulties in the lack of

support data as do other methods. Evaluation indicator selection and threshold level determination should be considered carefully because the optimization of network types and structure possesses great promise. Wen and Cao [62] combined environmental factors, functional groups, and trophic levels to establish an ANN model in which to study the stability of complex ecosystems. It used 90 datasets to train and test the model. They found that the actual network output and desired output were well-fitted, where the network training error was only 0.005. Li and Zhang [63] set up a comprehensive assessment model of townlet eco-environmental quality based upon BP-ANN. Their aim was to address problems concerning townlet eco-environmental quality assessment in China. The training sample of the model only requires choosing the rank classification criterion of the eco-environmental quality assessment. After training, the weights and thresholds of the network model were able to evaluate the monitoring samples, and it was found that the model exhibited high generality. Li et al. [64] also reported that they applied a BP-ANN model to predict the remote sensing background value in a particular ecosystem.

The ANN model possesses great flexibility in terms of risk prediction, and either linear or nonlinear mathematical functions of risk can be modeled by ANNs. Chen et al. [65] used a BP neural network to study the probability of housing preservation within forest fires. The input parameter was divided into two separate parts (A and B). The A model applied a binary variable, and the B model applied language semantics. The interrelated coefficients between the predicted values and the sample values were 0.989 and 0.968, respectively, indicating a good prediction result. Jiang et al. [66] used the ANN method to study the relationship between occurrence or the spread of forest fire and environmental factors. They used VLBP with MATLAB to train the data and established two risk models: the fire ignition model and the forest fire spread model. They found that forest fire risk forecasting based upon conventional meteorological factors was too idealistic. Significant changes will occur in meteorological factors influenced by topography. The ANN model resolved issues of excessive noise within data acquisition when 3S (GPS, RS and GIS) technology was used to study fire behavior [66]. Worner and Gevrey [67] reported that they used an ANN to model global insect pest species assemblages to determine invasion risk.

3 Discussion

3.1 Ongoing issues and future use

Arguments concerning ANNs being a type of “black box” approach are ongoing. ANNs have the following advantages: ANNs can approximate any complicated nonlinear relation; because all quantitative or qualitative information is stored within the network of neurons, they are strongly robust and fault-tolerant; they use a parallel distributed

processing approach, making it possible to quickly carry out large operations; they can learn and adapt unknown or uncertain systems; and they can manage quantitative and qualitative knowledge [68]. Their practical use has shown that the ANN model is superior to other traditional modeling methods in terms of data processing speed and accuracy in solving nonlinear problems. Especially in the case of incomplete information, they possess a strong capacity in pattern recognition, program decision making, and knowledge processing [69].

ANNs possess a complex architecture and unsurpassed network geometry. They may be able to simulate a set of data with good results while an opposite effect may occur with other sets of data. This condition derives from the nonlinear nature of ANNs, leading to over-fitness of data. The best hidden layer or the number of nodes are dependent upon their construction and repeated testing. The focal point of the BP algorithm will not be directed to a minimum during training if the number of hidden layer nodes is too small. Conversely, too many hidden nodes within a network will lead to an over-fitness of data. Over-fitness will always be an unavoidable issue with respect to the research or application of ANNs.

There is little doubt that the many advantages of ANNs open a new window into the vast prospects on global change and ecological research. For example, they have the ability to adapt to external environments through study, modal recognition and comprehensive reasoning, strong fault tolerance, the distributed storage of knowledge, and parallel structure and processing [70]. Certain problems, however, still exist. Obvious limitations are apparent compared with traditional models, such as ANN dependence upon sample quality and quantity, a slow convergence in their ability to learn, and its unstable network memory. The capacity of ANNs in relation to the parallel processing of information distribution storage mechanisms is not very clear. Moreover, no theoretical basis for how to choose a reasonable network structure exists. The application of ANNs in forecasting, network structure determination, network convergence improvement, and network training to prevent oscillations and convergence is determined typically by experiment or experience. Therefore, the network itself possesses great redundancy that can affect fitting and forecasting results. In addition, ANNs require numerous sample data to ensure extrapolation and reliability parameters. Such a large number of measured data are sometimes unavailable. Although simulation accuracy of ANN models is often far higher than multiple linear equations, they cannot replace mechanism-based models. This situation is similar for nonlinear equations. The real advantage of the ANN model is that it can simulate an unfamiliar system or one that cannot be realized by traditional models [10].

3.2 Potential applications of ANNs

Selecting a sound network structure can be problematic.

Yang [71] integrated the estimation algorithm sample complexity to update the method that applies the BP algorithm to improve ANN structure. A corresponding initial network structure could be generated based on the complexity of issues. The practical scope of the method, however, remains to be tested. The optimal selection of input parameters can also prove difficult. Kemp et al. [72] proposed a method using the sequential randomization of input parameters to determine the relative proportion each input variable contributes to the predictive ability of the ANN model. This is referred to as the holdback input randomization (HIPR) method and was assessed using a simulated dataset in which the relationship between input parameters and output parameters was known. The simulated datasets were generated with known linear, nonlinear, and collinear relationships. The HIPR method was conducted repeatedly on ANN models that were trained on these datasets. It was successful in predicting the ranking the importance of all datasets, and performed as well as or better than the recently-proposed connectivity weight method.

The primary purpose of ecological studies is to establish or confirm correlations among ecological parameters. The method reported by Kemp et al. [72] can be used to distinguish relationships among ecological parameter proportions, and provide a novel way to determine relationships among the correctness of parameter assumptions. Gevrey et al. [73] used seven methods to compare the relative contributions of the ANN model parameters. The partial derivatives method performed the best, followed by the profile method that contributes to configuration of the input variables. Next in order of performance were the weights and disturb methods, in which both were able to successfully classify and simplify the input parameters. Both methods, however, lacked stability. Two advanced stepwise regression models provided the same results, but the contributions were not sufficiently expressed. The traditional stepwise regression performed the worst. It is the opinion of Olden et al. [74] that Gevrey's findings [73] on true accuracy and precision is questionable, because true accuracy and precision are not readily available. Olden et al. [74] proposed the Monte-Carlo simulation to compare different methods in relation to input variable contribution. Their study suggests that only the weighting method can determine the importance of the correct level of the predictor variables because other methods can only determine the network in the first important variable or variables. The research of Gevrey [73] and Olden [74] shows that combining different methods with neural networks provide very different results. With the development of various new fields of study, especially the new artificial psychology discipline, ANNs will have increasingly important roles, and the potential of the ensuing applications is limitless [75].

To help understand ecological phenomena and to find new ways in which to solve problems, there is a need to develop and apply new methods in neural network exploration.

tion. Li and He [76] focused on cities within 13 northern Chinese provinces and used an ANN combined with SD and CA to establish land use/cover change in relation to spatial and temporal evolution of the dynamic simulation model. They then used the model to simulate spatial and temporal characteristics and the variety of land use/cover change types within the study areas. The improved accuracy of the simulation model reached 74%. This, to a certain extent, reflects the evolution of spatial patterns within large areas of land use/cover change. It provides a certain reference value of the complexity of land use/cover changes and ecosystem responses. Combined with a genetic algorithm to automatically select related input variables, D'heygere et al. [77] used a decision tree and an ANN to predict the presence or absence of benthic macroinvertebrate taxa. The predictive power of the models was assessed based upon three methods: the root mean squared error, correctly classified instances, and Cohen's kappa. Results show that the ANN model combined with correctly classified instances and Cohen's kappa provide an overall good forecast capacity.

One of the primary interests for modelers in terms of data assimilation techniques is the potential to highlight model deficiencies and uncertainties. Being able to include all the sources of uncertainty within a rigorous statistical framework represents a critical advantage. Abramowitz et al. [78] used an ANN linked to meteorological forcing and measured fluxes to provide benchmark tests against which to assess performance of several land surface models (LSMs). ANN performance was generally superior to that of LSM, which produced systematic errors in the fluxes of sensible heat, water vapor, and CO₂ at five test FLUXNET sites. These errors could not be eliminated using parameter optimization, and it appears that structural improvements to LSM are required before its performance can match the ANN benchmark. Moreover, predictions using LSM may only be satisfactory in certain parts of bioclimatic space and not in others. Abramowitz et al. [78] used self-organizing maps to divide climate space into distinct region sets to help identify conditions under which model bias is greatest, thereby assisting with the "detective work" to help improve model performance. With regard to climate change, factor interactions can influence how the soil respiration rate is affected by temperature and humidity, but they can also be influenced by other factor controls such as litter, soil depth, and soil pH value. Currently applied neural network models, however, seldom consider these factors.

Further improvements in ANN research will require time and heightened efforts, but like the human brain, the developmental potential for ANNs is enormous. ANNs combined with evolutionary computation of genetic algorithms, wavelet analysis and fuzzy system theory have become important research directions [79]. For example, fuzzy logic is good at managing structured problems. However, ANNs can learn directly from the samples themselves, and can manage unstructured information more effectively. These

methods are still little understood or have not been yet applied to global climate change and ecological research.

ANNs are a useful tool for classification, modeling, and forecasting global climate change and ecological research, and their applications are growing. When compared with traditional statistical methods, ANNs perform more accurately and more rapidly in managing complex issues and in simulating nonlinear system behaviors. However, the application of the ANN method is still in its infancy; it is also flawed in its difficulties in explaining its "black box" behavior, overlong training times, and data over-fitting. ANNs will not entirely replace traditional methods. However, by integrating these different methods and technologies into a decision-support system, ANNs will be a useful tool in studies of global climate change and ecology in the 21st century.

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